Recognize basic emotional statesin speech by machine learning techniques using mel-frequency cepstral coefficient features

Article

Accepted Version

Emotional State Recognition for AI Smart Home Assistants using Mel-Frequency Cepstral Coefficient Features

Ningning Yang[a], Nilanjan Dey[b], R. Simon Sherratt[c] and Fuqian Shi[a,*]
[a]*First Affiliated Hospital of Wenzhou Medical University, Wenzhou 325035, China; 1062764811@qq.com*
[b]*Department of Information Technology, Techno India College of Technology, West Bengal 740000, India; neelanjan.dey@gmail.com*
[c] *Department of Biomedical Engineering, the University of Reading, RG6 6AY, UK; r.s.sherratt@reading.ac.uk*

Abstract. AI based Speech Recognition has been widely used in the consumer field for control of smart home personal assistants, with many such devices on the market. Smart home assistants that could detect the user's emotion would improve the communication between a user and the assistant enabling the assistant to offer more productive feedback. Thus, the aim of this work is to analyze emotional states in speech and propose a suitable algorithm considering performance verses complexity for deployment in smart home devices. The four emotional speeches were selected from the Berlin Emotional Database (EMO-DB) as experimental data, 26 MFCC features were extracted from each type of emotional speech to identify the emotions of happiness, anger, sadness and neutrality. Then, speaker-independent experiments for our Speech emotion Recognition (SER) were conducted by using the Back Propagation Neural Network (BPNN), Extreme Learning Machine (ELM), Probabilistic Neural Network (PNN) and Support Vector Machine (SVM). Synthesizing the recognition accuracy and processing time, this work shows that the performance of SVM was the best among the four methods as a good candidate to be deployed for SER in smart home devices. SVM achieved an overall accuracy of 92.4% while offering low computational requirements when training and testing. We conclude that the MFCC features and the SVM classification models used in speaker-independent experiments are highly effective in the automatic prediction of emotion.

Keywords: Emotion recognition, back propagation neural network, extreme learning machine, Mel-frequency cepstral coefficients, smart home, support vector machine

1. Introduction

Speech Emotion Recognition (SER) was first proposed in 1997 by Picard [1] and has attracted widespread attention. It is well known that language communication is the preferred method when communicating with others in daily life, and human language is first formed through speech. It can be said that speech plays a decisive supporting role in language. Human speech not only contains important semantic information, but also implies rich emotional information [2]. The aim of SER is to obtain the emotional states of a user derived from their speech [3], thereby achieving harmonious communication between humans or between humans and machines.

Emotion is a comprehensive state that occurs when an individual receives an internal or external stimulus, including physiological reaction, subjective experience and external behavior [4]. When the internal or external stimulus are consistent with a user's needs or requests, they will experience positive emotions, whereas negative emotions can be experienced with unpleasant experiences or distress.

The ability for consumer devices to detect emotion has been a hot research topic since 2006 with the introduction of an early music recommender system [5], and facial expression recognition [6] for personal

*Corresponding author. E-mail: sfq@wmu.edu.cn

cameras in 2010. The first emotion recognition systems in the consumer field appeared in 2011 that used a database [7], and then biofeedback [8]. While research into music recommender systems has been buoyant [9,10], other interesting systems for human emotion include lighting for emotion [11] and emotion aware service robots [12], [13]. Recent research indicates seamless human-device interaction [14]. With the advent of smart consumer home devices [15], consumers can live in their home for longer, safer [16] and to live healthier lifestyles [17].

McNally [18] presented six basic emotions - anger, disgust, fear, happiness, sadness, surprise, and these are widely used in current research. Emotion can be roughly divided into two forms: discrete and dimensional [19]. Discrete emotion description utilizes fixed labels to describe emotions, such as happiness, anger and sadness. The dimensional emotion description describes emotional attributes with points in multi-dimensional space, such as the arousal-valence model in two dimensions [20,21], the position - arousal–dominance model in three dimensions [22] and the Hevner emotion ring model [23]. The two emotion description methods have their own advantages. Discrete emotion description has been widely used for SER with its advantages of being simple and easy to understand. At present, the acoustic features have been widely applied to study SER, and many remarkable achievements have been made [24,25].

The emotional features based on acoustics can be roughly classified into three types: prosodic features, spectral features and sound quality features [26]. The prosodic features [27] can reflect the changes of intensity and intonation in speech. The commonly used prosodic features have duration, pitch and energy. The spectral features may be divided into linear spectral features and cepstral features. The linear spectral features include the linear predictor coefficient (LPC) and the log-frequency power coefficient (LFPC). The cepstral features [28] include the Mel-Frequency Cepstral Coefficient (MFCC) and the linear predictor cepstral coefficient (LPCC). Among them, the MFCC is the most commonly used spectral feature for SER because of its characteristics being similar to the human ear. Sound quality features have a great influence on the emotional state expressed in speech, and it mainly includes sounds from breathing, brightness and formant [29]. Acoustic features are typically extracted in frames and enable emotional recognition through simple statistical analysis.

The rapid development of SER cannot be separated from the support of computer technology. Advanced computer technology has laid a solid foundation for the development of SER [30]. The task of SER is to extract the characteristic parameters that can reflect emotions from speech signals and then find out the mapping relationship between these characteristic parameters and human emotions [31].

As shown in Figure 1, a SER system generally consists of three modules: speech acquisition module, feature extraction module and emotion recognition module [32]. Natural speech is imported into the system through the sensors in the speech acquisition module, and then transmitted to the feature extraction module to extract the emotional features. Finally, the emotion recognition module performs a determination process based on the emotional features extracted. Natural speech is greatly affected by external factors which may lead to a reduction of recognition accuracy. Therefore, before the SER system can be established, it is necessary to collect an emotional corpus according to emotion description methods and record a high-quality emotion speech database [33].

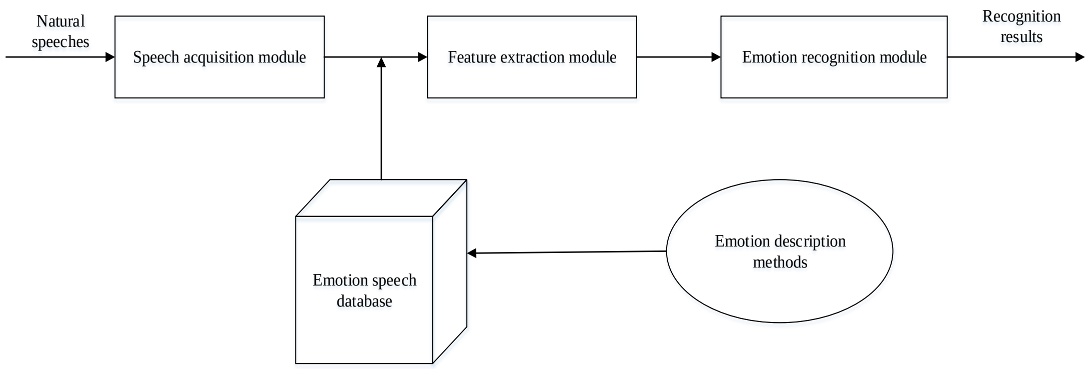

Fig. 1 Framework of a Speech Emotion Recognition (SER) system.

SER is essentially a pattern recognition problem; it can be realized through using the standard pattern classifiers [34]. At present, the classifiers commonly used for SER are: Artificial Neural Network (ANN), Support Vector Machine (SVM), Hidden Markov Model (HMM) and Gaussian Mixture Model (GMM). Rajisha et al. [39] extracted MFCCs, energy and pitch as emotional features and performed emotional recognition on the Malayalam emotion database using ANN and SVM as classifiers. The experimental results showed a classification accuracy of 88.4% for ANN and the classification accuracy of 78.2% for SVM. Sujatha and Ameena [40] conducted speaker-independent and speaker-dependent emotional recognition on the IITKGP-SESC and IITKGP-SEHSC databases. The recognition results using GMM, HMM and SVM as classifiers were that the recognition for seven different emotions in the speaker-dependent case was better than the speaker-independent case. In the speaker-independent case, GMM performed better on anger and surprise emotions and HMM performed better on disgust, fear and neutrality emotions. SVM achieved an average recognition accuracy of 86.6% for test samples of an unknown emotion. Lanjewar et al. [41] used GMM and K-Nearest Neighbor (KNN) as classifiers to identify six emotions in speech (including happiness, anger, sadness, fear, surprise and neutrality) using the Berlin Emotional Database (EMO-DB) [42]. GMM was more effective on the anger emotion with a 92% recognition rate while KNN achieved the highest recognition rate of 90% on happiness emotion. Although many classifiers can be applied to identify emotions in speech, each classifier has its own advantages and disadvantages, so the appropriate classification model needs to be selected according to the requirements.

This paper is concerned with defining suitable technology to enable smart home assistants, as a voice sensor, to predict the emotional state of a user, and in doing so offer more suitable responses to questions and home events. The work considers many classifiers and has found that the Support Vector Machine (SVM) is an excellent candidate for SER when considering both recognition performance, and real-time operation.

The rest of the article is structured as follows: The specific process to perform SER will be provided in Section II. Section III will introduce the testing methodology in detail. The experimental results and relevant discussion are presented in Section IV. Finally, conclusion and future works will be given in Section V.

2. Materials and Methods

In a practical system deployment, real-time user speech would be used. However, in order to compare and validate with other works, the EMO-DB database [42] has been used. The specific process of performing SER in this work is shown in Figure 2. The emotional speech selected from the database is first preprocessed to reduce noise interference and keep information integrity [43]. Then, extraction of emotional features is performed. The extracted data is then divided into training data and test data. The training data is used to train models and obtain classification rules whereas the test data is determined to belong to which type of emotions based on classification rules obtained from the training data. Finally, the recognition results are outputted. In this section, each step of SER is described in detail.

2.1. Emotion speech database

The EMO-DB database contains seven emotions: happiness, anger, sadness, neutrality, fear, disgust and boredom [44]. It was created using five male and five female actors who simulated emotions on five long sentences and five short sentences. Finally, the 535 speech recordings are retained after listening experiments of 10 males and 10 females with the length of each speech being 3~8s. The EMO-DB database was stored at a sampling rate of 16 kHz 16-bit quantization and stored in the common .wav file format.

2.2. Speech preprocessing

The purpose of preprocessing is to highlight the emotional information and reduce the impact of other information. The speech signal is a non-stationery and time-varying signal [45], but its characteristics remain basically unchanged in a short time range (generally considered to be 10-30ms), i.e. speech has short-term stability. Therefore, most systems adopt framing to preprocess speech [39]. Generally, the frame length is 10 to 30ms.

Before extracting emotional features, this work has used the Music Analysis, Retrieval and Synthesis for Audio Signals (MARSYAS) tool [46] to automatically frame speech, and its parameters are set as shown in Table 1.

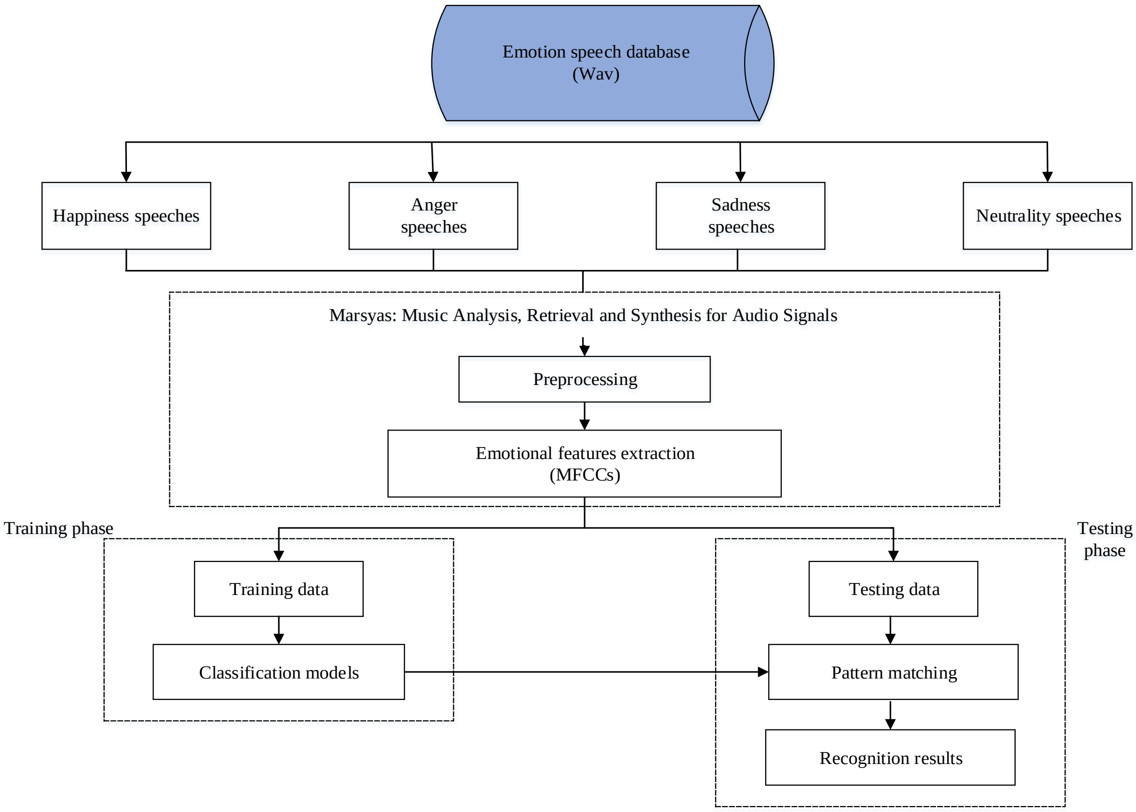

Fig. 2 Specific process of performing SER.

Table 1. Parameter Settings for Framing Speech

Parameter	Value
Sampling frequency	22.05 kHz
Down-sampling factor	1
Window size (*-ws*)	512 (sampling points)
Hop size (*-hp*)	512 (sampling points)

2.3. Feature extraction

2.3.1. Extracting features using MARSYAS

Feature extraction refers to the process of obtaining parameters which can describe characteristics of speech from a speech waveform [47]. In this work, we have used MARSYAS to extract 26 MFCC features from happiness, anger, sadness and neutrality speech in the EMO-DB database. MARSYAS is mainly used to extract the texture features of speech signals. When extracting MFCC features, we created four emotion audio sets (Happiness, Anger, Sadness and Neutrality). Then, 26 MFCC features were extracted from the audio sets that included the mean and standard deviation of the static MFCC and the 1~12 order MFCCs.

2.3.2. Mel-Frequency Cepstral Coefficients

MFCC is one of the characteristic parameters commonly used in SER and it is put forward based on the Mel filter. The Mel filter is designed according to the human ear hearing system. It considers the process and characteristic which humans make voices and human ear accepts voice [28]. The frequency of the Mel filter is termed the Mel frequency and it is consistent with the auditory characteristics of the human ear and closely related to the actual voice frequency. The Mel frequency has a nonlinear relationship with frequency [33]. The specific relationship between the Mel frequency and the actual frequency is:

$$f_{Mel} = 2595 \times lg\left(1 + \frac{f}{700}\right) \tag{1}$$

where f is the actual speech frequency (Hz). The MFCC is the prediction cepstral coefficient obtained on the Mel frequency. The steps of extracting MFCC are:

Step 1: Preprocessing: the finite discrete signal $(x_i(n))$ is obtained after framing, where *i* represents the *i*-th frame.

Step 2: The Fast Fourier Transform (FFT) is applied to each frame:

$$X(i,k) = FFT[x_i(n)] = \sum_{n=0}^{N-1} x_i(n) W_N^{kn} \quad k = 0,1,\dots,N-1 \tag{2}$$

where N is the number of sampling points in each frame. Then the power spectrum is obtained:

$$E(i,k) = [X(i,k)]^2 \tag{3}$$

Step 3: Calculate the energy through the Mel filter.

$$S(i,m) = \sum_{k=0}^{N-1} E(i,k) H_m(k) \tag{4}$$

Step 4: Calculate MFCC using the Discrete Cosine Transform (DCT).

$$MFCC(i,n) = \sqrt{\frac{2}{M}} \sum_{m=0}^{M-1} log[S(i,m)] \cos\left(\frac{\pi n(m-0.5)}{M}\right) \quad n = 1,2,\dots,L \tag{5}$$

where n represents the order of the MFCC, and L is usually taken as 12. M is the number of Mel filters.

2.4. Classification model

2.4.1. Back Propagation Neural Network (BPNN)

BPNN is a multi-layer feedforward neural network [48] famous for being a back propagation (BP) algorithm. The BPNN algorithm includes two processes: forward transmission of signals and back propagation of errors [49]. In the forward transmission speech signals are transmitted from the input layer through the hidden layer to calculate the outputs of output layer. In back propagation of errors, the output error of network is first calculated as:

$$E = \frac{1}{2} \sum_{k=1}^{L} (T_k - O_k)^2 \quad k = 1,2,\dots,m \tag{6}$$

where T_k and O_k represent the expected output and the actual output of the k-th node in the output layer respectively. Then, according to the gradient descent algorithm **Error! Reference source not found.**, the adjustment formula for the weights ($w_{ki}\&w_{ij}$) and thresholds ($a_k\&\theta_i$) are obtained:

$$w_{ki} = w_{ki} + \Delta w_{ki} = w_{ki} - \eta \frac{\partial E}{\partial w_{ki}} \tag{7}$$

$$a_k = a_k + \Delta a_k = a_k - \eta \frac{\partial E}{\partial a_k} \tag{8}$$

$$w_{ij} = w_{ij} + \Delta w_{ij} = w_{ij} - \eta \frac{\partial E}{\partial w_{ij}} \tag{9}$$

$$\theta_i = \theta_i + \Delta \theta_i = \theta_i - \eta \frac{\partial E}{\partial \theta_i} \tag{10}$$

where w_{ki} represents the weight between the k-th node in the output layer and the i-th node in the hidden layer, a_k represents the threshold of the k-th node in the output layer, w_{ij} represents the weight between the i-th node in the hidden layer and the j-th node in the input layer, θ_i represents the threshold of the i-th node in the hidden layer and η represents the learning rate.

2.4.2. Extreme Learning Machine (ELM)

ELM was proposed in 2004 by Huang [51]. Different from traditional algorithms (such as BP algorithm), ELM randomly generates the weights between the input layer, the hidden layer, and the thresholds of the hidden layer node. The thresholds do not need to be adjusted during the training process. It only needs to set the number of nodes in the hidden layer to determine the weights between the hidden layer and the output layer by solving the equation set [52].

Let the number of neurons in the input layer, hidden layer and output layer be n, l and m respectively, the weight matrix between the hidden layer and the input layer is $\boldsymbol{w} = [w_{ij}]_{l\times n}$, the weight matrix between the hidden layer and the output layer is $\boldsymbol{\beta} = [\beta_{ik}]_{\boldsymbol{l\times m}}$, the threshold matrix of the hidden layer is $\boldsymbol{b} = [b_i]_{l\times 1}$, the input sample is $\boldsymbol{x} = [x_j]_{n\times 1}$, and the activation function of the hidden layer is $g(x)$, then the actual output matrix of the output layer ($\boldsymbol{O} = [O_k]_{m\times 1}$) can be expressed by:

$$\boldsymbol{H\beta} = \boldsymbol{O^T} \tag{11}$$

where $\boldsymbol{H} = [g(\boldsymbol{w}_i\mathbf{x} + \boldsymbol{b_i})]_{\boldsymbol{1\times l}}$ is the output matrix of the hidden layer, $\boldsymbol{w}_i$ represents the i-th row of matrix $\boldsymbol{w}$; $\boldsymbol{O^T}$ is the transpose of the matrix $\boldsymbol{O}$. The ELM optimization not only minimizes the network error, but also minimizes the weights between the hidden layer and the output layer. Therefore, the optimization objective equation is:

$$\min_{\beta} \parallel \boldsymbol{H\beta} - \boldsymbol{T^T} \parallel \tag{12}$$

where $\boldsymbol{T} = [T_k]_{m\times 1}$ is the expected output matrix of the output layer, $\boldsymbol{T^T}$ is the transpose of the matrix $\boldsymbol{T}$. Finally, the weights of between the hidden layer and the output layer is given by:

$$\boldsymbol{\hat{\beta}} = \boldsymbol{H^+T^T} \tag{13}$$

where $\boldsymbol{H^+}$ is the Moore-Penrose generalized inverse of matrix $\boldsymbol{H}$.

2.4.3. Probabilistic Neural Network (PNN)

The theoretical basis of PNN is the Bayesian decision theory and Parzen probability density estimation [53]. During training, PNN does not need error back propagation like BPNN as it only contains a forward calculation process [54]. PNN consists of an input layer, pattern layer, accumulation layer and output layer. The first layer is the input layer responsible for transmitting the feature vectors in the training samples to the network. The number of neurons in this layer is equal to the dimension of the feature vector. The second layer is the pattern layer, its function is to calculate the matching relationship between the feature vector and each category, and the number of neurons in this layer is same with the sum of training samples. The output of the *j*-th neuron of the *i*-th category in the pattern layer is:

$$\phi_{ij}(\boldsymbol{x}) = \frac{1}{(2\pi)^{\frac{1}{2}}\sigma^d} exp\left[-\frac{(\boldsymbol{x}-\boldsymbol{c_{ij}})(\boldsymbol{x}-\boldsymbol{c_{ij}})^T}{\sigma^2}\right]$$
$$i = 1,2,\dots,M; j = 1,2,\dots,L_i \qquad (14)$$

where $\boldsymbol{x}$ represents the input vector with d as its dimension, $\boldsymbol{c_{ij}}$ represents the center of the *j*-th neuron of the *i*-th category in the pattern layer, *M* is the number of categories in the training samples, L_i is the number of neurons of the *i*-th category in the pattern layer, σ is the smoothing factor, it plays an important role in network performance.

The third layer is the accumulation layer, it accumulates the probability density function of each category according to:

$$v_i = \frac{1}{L_i}\sum_{j=1}^{L_i}\phi_{ij} \qquad (15)$$

where v_i represents the output of the *i*-th category. The number of neurons in the accumulation layer is equal to *M*. Finally, the adjudicative result is output by the output layer. There is only one '1' in the output result and the rest are '0'. The output of the class with the largest probability density function is 1, that is:

$$y = argmax(v_i) \qquad (16)$$

2.4.4. Support Vector Machine (SVM)

SVM is a supervised machine learning method based on statistical learning theory and structural risk minimization [55]. The basic idea of SVM is - for the nonlinear and separable problem of the input space, the input vector is mapped to the high-dimensional feature space through selecting the appropriate kernel function. Then, the optimal separating hyperplane is constructed in the high-dimensional feature space to make the corresponding sample space linearly separable [56]. The objective function corresponding to the nonlinear separable SVM is:

$$\begin{cases} min\left(\frac{1}{2}\boldsymbol{w}^T\boldsymbol{w} + C\sum_{i=1}^{N}\xi_i\right) \\ s.t. \boldsymbol{Y}_i(\boldsymbol{w}^T\boldsymbol{X}_i + b) + \xi_i \geq 1 \end{cases}$$
$$\xi_i > 0, i = 1,2,\dots,N \qquad (17)$$

where $\{\boldsymbol{X}_i, \boldsymbol{Y}_i\}$ represents the training sample set, $\boldsymbol{X}_i$ is the n dimensional feature vector, $\boldsymbol{Y}_i \in \{-1,1\}$ represents the sample category, *N* represents the number of the training samples, $\boldsymbol{w}$ is the weight vector, b is the classification threshold, $s.t.$ represents the constraint condition, *C* is the penalty coefficient, it controls the degree of punishment for the wrong classification samples and it has the effect of balancing complexity and loss error of the model, ξ_i is the relaxation factor which is used to control the classification surface to allow the existence of the wrong classification samples in classifying.

The input vectors $\boldsymbol{X}_i$ and $\boldsymbol{X}_j$ adopt the mapping function $\boldsymbol{\phi}(\cdot)$ from the data space to the feature space, and the kernel function transformation equation $(\boldsymbol{X}_i, \boldsymbol{X}_j) \to \mathrm{K}(\boldsymbol{X}_i, \boldsymbol{X}_j) = \boldsymbol{\phi}(\boldsymbol{X}_i)\cdot\boldsymbol{\phi}(\boldsymbol{X}_j)$ to get the optimal hyperplane function:

$$f(x) = sgn\left[\sum_{i=1}^{N}\alpha_i\boldsymbol{Y}_iK(\boldsymbol{X}_i, \boldsymbol{X}) + b\right] \qquad (18)$$

where α_i is the Lagrangian multiplier and $sgn(\cdot)$ is the sign function. Finally, the classification results are output according to the optimal hyperplane function.

The SVM algorithm is originally designed for binary classification. When dealing with multi-classification problems, it is necessary to construct a suitable multi-classification SVM. The common method for constructing multi-classification SVM is the one-to-one method, it is to design a SVM between any two classes, which can convert *c*-class classification patterns into $c(c-1)/2$ two-class classification patterns [57]. The four emotions of happiness, anger, sadness and neutrality in speech are classified, so six SVMs need to be built. Each SVM is used to identify any two emotions of the four emotions, namely happiness-anger, happiness-sadness, happiness-neutrality, anger-sadness, anger-neutrality and sadness-neutrality. When classifying an unknown sample, the six SVMs discriminate it, and finally the emotional category with the highest win frequency is taken as the emotion of the unknown sample. The win frequency for each class refers to the ratio between the number which the unknown sample is divided into this class and the total number which the unknown sample

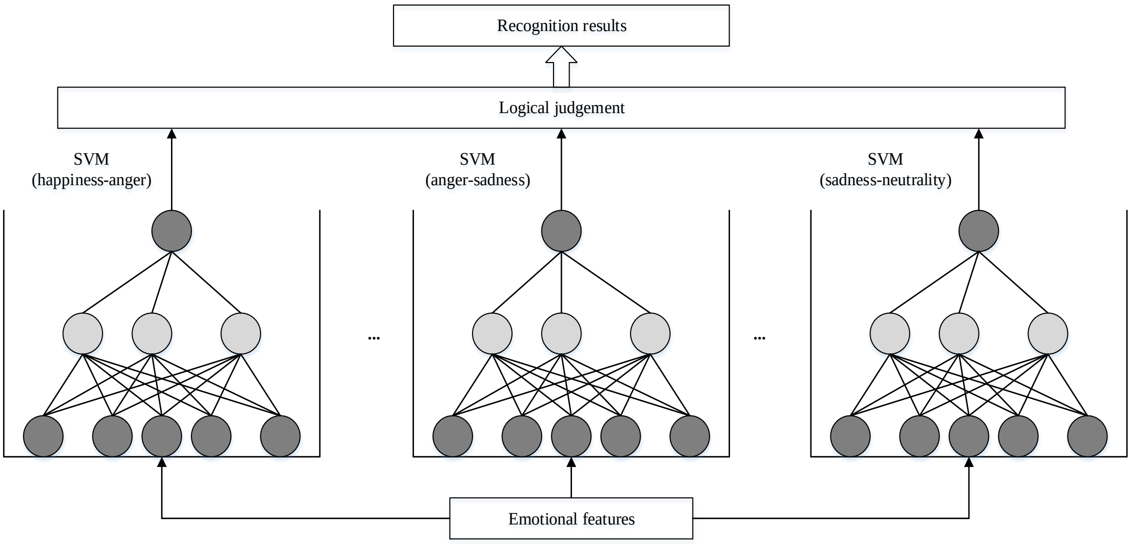

Fig. 3 The system of multi-classification SVM.

is divided into all classes. Figure 3 shows the system of multi-classification SVM.

3. Experiment setup

3.1. Data preprocessing

Four emotional speech patterns of happiness, anger, sadness and neutrality in the EMO-DB database were used to test the speaker-independent emotion recognition system. Each kind of emotional speech was extracted from the 500 groups of 26 MFCC features, of which 375 groups are selected as training data and 125 groups are used as test data. The training set included 1500 groups of feature data and the test set included 500 groups of feature data. Different types of emotional data were marked by happiness=1, anger=2, sadness=3 and neutrality=4. The emotional data extracted and stored in a group. The data group had 27 columns, the first column being the emotion label and the latter 26 columns were the emotional feature.

Before network training, normalization was applied to eliminate the difference in dimension and order of magnitude between data and reduce the network prediction error caused by them. The Min-Max method was used to normalize the experimental data as:

$$X_n = \frac{x_n - x_{min}}{x_{max} - x_{min}} \tag{19}$$

where x_n represents the original data, X_n represents the normalized data, and x_{min} and x_{max} are the minimum and maximum values of the original data respectively.

3.2. Parameter settings for training models

3.2.1. Parameter settings for BPNN training

For BPNN, the number of hidden layer nodes had a great influence on the network prediction accuracy. A small number of nodes led to a low recognition accuracy, and the large number of nodes resulted in over-fitting. The optimum number of hidden layer nodes, *l* was:

$$l < \sqrt{m+n} + b \tag{20}$$

where n is the number of input layer nodes, m is the number of output layer nodes, and b is a constant between [0, 10].

The number of nodes in the input layer and output layer were automatically determined according to the input matrix and the output matrix when building the BPNN. Through comparing the preliminary results, the number of hidden layer nodes was determined as 13. The specific parameter settings of the BPNN was as shown in Table 2.

Table 2. Parameter Settings for BPNN

Network parameters	**Value**
Number of hidden layer nodes (*l*)	13
Number of network training (*epochs*)	150
Mean squared error goal (*goal*)	0.0001
Learning rate (*lr*)	0.2

3.2.2. Parameter settings for ELM training

The parameter settings of ELM are shown in Table 3. The number of neurons in the hidden layer was also is an important parameter that affected the performance of the ELM. It was generally much smaller than the number of training samples. When using ELM to conduct the speaker-independent experiments, the number of hidden layer neurons, *N*, was set to 100. *TF* represents the activation function of the hidden layer neurons, and its value was set to 'sig'. *TYPE* is the application type of ELM, which takes a value of 0 for regression and 1 for classification. The experiments conducted in this article belong to the classification problem, so the value of *TYPE* was set to 1.

Table 3. Parameter Settings for ELM

Network parameters	**Value**
Number of hidden layer nodes (***N***)	100
Activation function of hidden layer nodes (*TF*)	'sig'
Application type of ELM (*TYPE*)	1

3.2.3. Parameter settings for PNN training

For PNN, only parameter *Spread* was needed to be set. *Spread* is the expansion coefficient of radial basis function. When its value was close to 0, the created PNN was equal to a nearest neighbor classifier. When its value was large, the created PNN constituted the adjacent classifier to several training samples. After trying different values of *Spread*, it was set to 0.3 for this work.

3.2.4. Parameter settings for SVM training

The LINSVM toolbox [58] was used to conduct the SVM experiment. When using the SVM to perform classification experiments, the ideal prediction results are obtained through adjusting the network parameters, among which the most important parameters were the penalty parameter, *c*, and the kernel function parameter, *g*. Cross Validation (CV) was used to verify the performance of classifiers and we used it to obtain the values *c* and *g*. The specific method was - let *c* and *g* take values in a certain range, then the classification accuracy under the selected c and g was obtained by using the training set as the data set and CV method. The group *c* and *g* which created the classification accuracy of training set to be the highest were then selected. The parameters *c* and *g* were determined by different ranges of values, the value range of *c* was:

$$2^{-2},\ 2^{-1.5},\ \ldots, 2^{3.5},\ 2^{4}$$

and the value range of *g* was:

$$2^{-4},\ 2^{-3.5},\ \ldots, 2^{3.5},\ 2^{4}$$

After using CV method, the best values for *c* and *g* were 4 and 4 respectively, and the highest recognition accuracy of training set was 92.2%. Other parameters of SVM were set as default values.

3.3. Experimental platforms

All experiments are conducted on a standard PC using standard mathematical design software and the MARSYAS framework.

4. Results and discussion

To avoid overfitting and underfitting problems, we adopted the following measures: firstly, we randomly selected emotional speech contained different texts and different persons before extracting speech features; secondly, we used random allocation methods to separate training set and test set, and the train set was shuffled before training; thirdly, when training models, we set the training epoch to avoid overfitting due to excessive time. For SER, the features extracted from each type of emotional speech were regarded as a pattern. Then the classification results were obtained by matching with existing reference patterns. BPNN, ELM, PNN and SVM were used as recognizers to carry out the speaker-independent emotion recognition experiments in this work. To intuitively reflect the property of each classifier, the confusion matrix has been applied to show the experimental results.

Table 4 shows the recognition results of four emotions when the BPNN was used as a classifier. It can be seen from Table 6 that 95 happiness samples were correctly identified out of 125. The numbers of samples misidentified as anger emotion, sadness emotion and neutrality state were 13, 7 and 10 respectively. Among the 125 anger samples, 89 samples were correctly recognized with most of the remaining samples incorrectly identified as happiness. For the recognition of sadness, there were 111 samples correctly identified and 14 samples incorrectly identified. Under the neutrality state, the number of samples correctly recognized was 94 with other samples largely misidentified as sadness. Interestingly, the BPNN results showed that anger was easily confused with happiness, and neutrality state was easily recognized as sadness. The recognition accuracy of four emotions when using BPNN as a classifier is indicted in Table 5.

Table 4. Recognition Results of BPNN Classifier

Actual emotion	Predicted happiness	Predicted anger	Predicted sadness	Predicted neutrality
Happiness	95	13	7	10
Anger	22	89	6	8
Sadness	3	4	111	7
Neutrality	2	7	22	94

Table 5. Recognition Accuracy of BPNN Classifier

Emotion class	Recognition accuracy (%)	Total/True
Happiness	76	125/95
Anger	71.2	125/89
Sadness	88.8	125/111
Neutrality	75.2	125/94

Table 6. Recognition Results of ELM Classifier

Actual emotion	Predicted happiness	Predicted anger	Predicted sadness	Predicted neutrality
Happiness	92	17	6	10
Anger	22	98	1	4
Sadness	5	7	106	7
Neutrality	11	4	14	96

Table 7. Recognition Accuracy of ELM Classifier

Emotion class	Recognition accuracy (%)	Total/True
Happiness	73.6	125/92
Anger	78.4	125/98
Sadness	84.8	125/106
Neutrality	76.8	125/96

Table 8. Recognition Results of PNN Classifier

Actual emotion	Predicted happiness	Predicted anger	Predicted sadness	Predicted neutrality
Happiness	110	6	7	2
Anger	16	83	8	18
Sadness	0	1	111	13
Neutrality	6	0	18	101

Table 9. Recognition Accuracy of PNN Classifier

Emotion class	Recognition accuracy (%)	Total/True
Happiness	88	125/110
Anger	66.4	125/83
Sadness	88.8	125/111
Neutrality	80.8	125/101

Compared with BPNN, the recognition effect of ELM was significantly improved. The classification results and the recognition accuracy are shown in Table 6 and Table 7 respectively. As can be seen, the recognition of sadness emotion was the best among the four emotions with 106 sadness samples identified correctly and the recognition accuracy reaches 84.8%. The recognition rates of anger and neutrality state were more than 75% whereas the recognition results for happiness was not as good. In addition, we obtain conclusions similar with BPNN where confusion arises between anger and happiness.

Tables 8 and Table 9 represent the classification results of four emotions when using PNN as a recognizer. It can be seen that the PNN does not perform well on the identification of the angry emotion. The recognition performance for the other three emotions are better than ELM and BPNN.

From the recognition results of SVM shown in Tables 10 and Table 11, the recognition of happiness is the best performing among the four emotions at 96.8%. The predictions for the sadness emotion and neutrality state achieve better than 90%. The number of anger samples correctly identified is the worst amongst the four emotional states but the best across all the classifiers tested.

Table 10. Recognition Results of SVM Classifier

Actual emotion	Predicted happiness	Predicted anger	Predicted sadness	Predicted neutrality
Happiness	121	3	1	-
Anger	13	110	-	2
Sadness	1	3	116	5
Neutrality	4	3	3	115

Table 11. Recognition Accuracy of SVM Classifier

Emotion class	Recognition accuracy (%)	Total/True
Happiness	96.8	125/121
Anger	88	125/110
Sadness	92.8	125/116
Neutrality	92	125/115

To objectively compare the performance of BPNN, ELM, PNN and SVM, their overall accuracy is presented in Table 12. When conducting the speaker-independent emotion recognition experiments, the performance of the BPNN, ELM and PNN were not significantly different. However, the recognition property utilizing SVM is the best and its overall accuracy was up to 92.4% across the four emotions. Compared with other three algorithms, the overall accuracy of SER system increases by 11.4% to 14.6%.

In order to understand the computational requirements, we also recorded the training time and the testing time for each classifier, as shown in Table 13. The training time and testing time of ELM was the shortest, but the training time and testing time of SVM is still impressive and certainly within requirements for real-time operation. Combined with the accuracy indicators of SVM as detailed above, then SVM clearly realizes the best overall performance among the four tested classifiers. Although the emotional classification performance of BPNN, ELM and PNN were not as good as SVM, they must still be considered as potential models for a practical SER system. Each model has its own merits and demerits, and many external factors may lead to a decline in network performance. Therefore, it is not only required to select a suitable model according to specifications, but designers must attempt to avoid interference of external factors on the system in order to obtain the optimal results.

Table 12. Overall Accuracy of Classifiers

Classifiers	**Overall accuracy (%)**
BPNN	77.8
ELM	78.4
PNN	81
SVM	92.4

Table 13. Training Time and Testing Time of the Four Classifiers

	BPNN (secs)	**ELM (secs)**	**PNN (secs)**	**SVM (secs)**
Training time	2.9343	0.0671	1.2515	0.2532
Testing time	0.3235	0.0242	0.5990	0.0658

5. Conclusions

In this article, the Mel-Frequency Cepstral Coefficient (MFCC) features were applied to conduct speaker-independent experiments for a Speech Emotion Recognition (SER) element for an AI based smart home assistant to predict the user's emotional state. To study the expression effect of MFCC features on speech emotion in detail, we used BPNN, ELM, PNN and SVM as classifiers to identify the four emotions of happiness, anger, sadness and neutrality from the EMO-DB database. By considering accuracy and computational time indicators, the overall performance of SVM was clearly the best compared with other three models and an ideal candidate to be used with in smart home assistants. When using SVM as a classifier, the recognition accuracy of happiness emotion, anger emotion, sadness emotion and neutrality state were 96.8%, 88%, 92.8% and 92% respectively, and the training time and testing time consumed were relatively short indicating an ability to operate in real-time and as an excellent candidate for enabling AI smart home assistants to predict the emotion of the user with the aim to improve assistance and feedback. Despite the recognition effect of BPNN, ELM and PNN being not as good as SVM, they can meet common identification requirements which suggests that the emotional characteristics extracted are effective.

In future work, it will be a top priority to collect and record enough emotional speech recordings to avoid the low recognition accuracy of a classifier from insufficient experimental data, and to report on the acceptance of real-time identification with consumers. Furthermore, we will attempt to extract multiple types of acoustic features to fuse features of advanced classification models for SER. Other indicators will also be added to evaluate the performance of a classification model synthetically.

References

[1] S. Poria, E. Cambria, R. Bajpai, and A. Hussain, "A review of affective computing: from unimodal analysis to multimodal fusion," Information Fusion, vol. 37, pp. 98–125, Sep. 2017, 10.1016/j.inffus.2017.02.003.

[2] Y. Sun and X. Y. Zhang, "Characteristics of human auditory model based on compensation of glottal features in speech emotion recognition," Future Generation Computer Systems, vol. 81, pp. 291–296, Apr. 2018, DOI. 10.1016/j.future.2017.10.002.

[3] T. Özseven, "Investigation of the effect of spectrogram images and different texture analysis methods on speech emotion recognition," Applied Acoustics, vol. 142, pp. 70–77, Dec. 2018, 10.1016/j.apacoust.2018.08.003.

[4] T. K. L. Hui and S. Sherratt, "Coverage of emotion recognition for common wearable biosensors," Sensors, vol. 8, no. 2, 30, Mar. 2018, 10.3390/bios8020030.

[5] X. Zhu, Y.-Y. Shi, H.-G. Kim and K.-W. Eom, "An integrated music recommendation system," IEEE Trans. Consum. Electron., vol. CE-52, no. 3, pp. 612–618, Aug. 2006, 10.1109/TCE.2006.1706489.

[6] I. Bacivarov, P. Corcoran and M. Ionita, "Smart cameras: 2D affine models for determining subject facial expressions," IEEE Trans. Consum. Electron., vol. CE-56, no. 2, pp. 298–297, May 2010, 10.1109/TCE.2010.5505930.

[7] W.-J. Yoon and K.-S. Park, "Building robust emotion recognition system on heterogeneous speech databases," IEEE Trans. Consum. Electron., vol. CE-57, no. 2, pp. 747–750, May 2011, 10.1109/TCE.2011.5955217.

[8] D. K. Kim, J. Kim, E. C. Lim and M. Whang, Y. Cho, "Interactive emotional content communications system using portable wireless biofeedback device," IEEE Trans. Consum.

Electron., vol. CE-57, no. 4, pp. 1929–1936, Nov. 2011, 10.1109/TCE.2011.6131173.
[9] K. Yoon, J. Lee and M.-U. Kim, “Music recommendation system using emotion triggering low-level features,” IEEE Trans. Consum. Electron., vol. CE-58, no. 2, pp. 612–618, May 2012, 10.1109/TCE.2012.6227467.
[10] R. L. Rosa, D. Z. Rodriguez and G. Bressan, “Music recommendation system based on user's sentiments extracted from social networks,” IEEE Trans. Consum. Electron., vol. CE-61, no. 3, pp. 359–367, Aug. 2015, 10.1109/TCE.2015.7298296.
[11] D. K. Kim, S. Ahn, S. Park and M. Whang, “Interactive emotional lighting system using physiological signals,” IEEE Trans. Consum. Electron., vol. CE-59, no. 4, pp. 765–771, Nov. 2013, 10.1109/TCE.2013.6689687.
[12] J.-S. Park, J.-H. Kim and Y.-H. Oh, “Feature vector classification-based speech emotion recognition for service robots,” IEEE Trans. Consum. Electron., vol. CE-55, no. 3, pp. 1590–1596, Aug. 2009, 10.1109/TCE.2009.5278031.
[13] D.-S. Kim, S.-S. Lee and B.-H. Chol, “A real-time stereo depth extraction hardware for intelligent home assistant robot,” IEEE Trans. Consum. Electron., vol. CE-56, no. 3, pp. 1782–1788, Aug. 2010, 10.1109/TCE.2010.5606326.
[14] E. Rubio-Drosdov, D. Diaz-Sanchez, F. Almenarez, P. Arias-Cabarcos and A. Marin, “Seamless human-device interaction in the internet of things,” IEEE Trans. Consum. Electron., vol. CE-63, no. 4, pp. 490–498, Nov. 2017, 10.1109/TCE.2017.015076.
[15] T. Perumal, A. R. Ramli and C. Y. Leong, “Design and implementation of SOAP-based residential management for smart home systems,” IEEE Trans. Consum. Electron., vol. CE-54, no. 2, pp. 453–459, May 2008, 10.1109/TCE.2008.4560114.
[16] J. Wang, Z. Zhang, B. Li, S. Lee and R. S. Sherratt, “An enhanced fall detection system for elderly person monitoring using consumer home networks,” IEEE Trans. Consum. Electron., vol. CE-60, no. 1, pp. 23–29, Feb. 2014, 10.1109/TCE.2014.6780921.
[17] N Dey, A. S. Ashour, F. Shi, S. J. Fong and R. S. Sherratt, “Developing residential wireless sensor networks for ECG healthcare monitoring,” IEEE Trans. Consum. Electron., vol. CE-63, no. 4, pp. 442–449, Nov. 2017, 10.1109/TCE.2017.015063.
[18] R. J. McNally, “Handbook of cognition and emotion,” British J. Psychiatry, vol. 176, no. 5, Jan. 1999, 10.1002/0470013494.
[19] S. Hamann, “Mapping discrete and dimensional emotions onto the brain: controversies and consensus,” Trends in Cognitive Sciences, vol. 16, no. 9, pp. 458–466, Sep. 2012, 10.1016/j.tics.2012.07.006.
[20] C. Chih-Hao, L. Wei-Po, and H. Jhih-Yuan, “Tracking and recognizing emotions in short text messages from online chatting services,” Information Processing & Management, vol. 54, no. 6, pp. 1325–1344, Nov. 2018, 10.1016/j.ipm.2018.05.008.
[21] F. Shi, N. Dey, A. S. Ashour, D. Sifaki-Pistolla and R. S. Sherratt, “Meta-KANSEI modeling with valence-arousal fMRI dataset of brain,” Cognitive Computation, Dec. 2018, 10.1007/s12559-018-9614-5.
[22] W. Dai, D. Han, Y. Dai, and D. Xu, “Emotion recognition and affective computing on vocal social media,” Information & Management, vol. 52, no. 7, pp. 777–788, Nov. 2015, 10.1016/j.im.2015.02.003.
[23] B. Xing, K. Zhang, S. Sun, L. Zhang, Z. Gao, and J. Wang, “Emotion-driven Chinese folk music-image retrieval based on DE-SVM,” Neurocomputing, vol. 148, pp. 619–627, Jan. 2015, 10.1016/j.neucom.2014.08.007.
[24] I. Zualkernan, F. Aloul, S. Shapsough, A. Hesham, and Y. El-Khorzaty, “Emotion recognition using mobile phones,” Computers & Electrical Engineering, vol. 60, pp. 1–13, May 2017, 10.1016/j.compeleceng.2017.05.004.
[25] J. B. Alonso, J. Cabrera, C. M. Travieso, K. López-de-Ipiña, and A. Sánchez-Medina, “Continuous tracking of the emotion temperature,” Neurocomputing, vol. 255, pp. 17–25, Sep. 2017, 10.1016/j.neucom.2016.06.093.
[26] L. Nanni, Y. M. G. Costa, D. R. Lucio, C. N. Silla, and S. Brahnam, “Combining visual and acoustic features for audio classification tasks,” Pattern Recognition Lett., vol. 88, pp. 49–56, Mar. 2017, 10.1016/j.patrec.2017.01.013.
[27] M. Kraxenberger, W. Menninghaus, A. Roth, and M. Scharinger, “Prosody-based sound-emotion associations in poetry,” Frontiers in Psychology, vol. 9, pp. 1284–1284, Jul. 2018, 10.3389/fpsyg.2018.01284.
[28] S. Lalitha, D. Geyasruti, R. Narayanan, and M. Shravani, “Emotion Detection Using MFCC and Cepstrum Features,” Procedia Computer Science, vol. 70, pp. 29–35, Dec. 2015, 10.1016/j.procs.2015.10.020.
[29] A. Jacob, “Speech emotion recognition based on minimal voice quality features,” in Proc. ICCSP, Melmaruvathur, India, 2016, pp. 0886–0890, 10.1109/ICCSP.2016.7754275.
[30] L. A. Perez-Gaspar, S. O. Caballero-Morales, and F. Trujillo-Romero, “Multimodal emotion recognition with evolutionary computation for human-robot interaction,” Expert Systems with Applications, vol. 66, pp. 42–61, Dec. 2016, 10.1016/j.eswa.2016.08.047.
[31] A. Davletcharova, S. Sugathan, B. Abraham, and A. P. James, “Detection and analysis of emotion from speech signals,” Procedia Computer Science, vol. 58, pp. 91–96, Jun. 2015, 10.1016/j.procs.2015.08.032.
[32] P. A. Abhang, B. W. Gawali, and S. C. Mehrotra, “Chapter 7 - Proposed EEG/speech-based emotion recognition system: a case study,” Introduction to EEG- and Speech-Based Emotion Recognition, pp. 127–163, 2016, 10.1016/B978-0-12-804490-2.00007-5.
[33] S. Basu, J. Chakraborty, A. Bag, and M. Aftabuddin, “A review on emotion recognition using speech,” in Proc. ICICCT, Coimbatore, India, 2017, pp. 109–114, 10.1109/ICICCT.2017.7975169.
[34] R. C. Guido, J. C. Pereira, and J. F. W. Slaets, “Emergent artificial intelligence approaches for pattern recognition in speech and language processing,” Computer Speech & Language, vol. 24, no. 3, pp. 431–432, Jul. 2010, 10.1016/j.csl.2010.03.002.
[35] T. M. Rajisha, A. P. Sunija, and K. S. Riyas, “Performance analysis of Malayalam language speech emotion recognition system using ANN/SVM,” Procedia Technology, vol. 24, pp. 1097–1104, Dec. 2016, 10.1016/j.protcy.2016.05.242.
[36] B. Sujatha and O. Ameena, “Speech Emotion Recognition using HMM, GMM and SVM,” Int. J. Professional Engineering Studies, vol. 6, no. 3, pp. 311–318, Jul. 2016.
[37] R. B. Lanjewar, S. Mathurkar, and N. Patel, “Implementation and comparison of speech emotion recognition system using Gaussian mixture model (GMM) and k-nearest neighbor (K-NN) techniques,” Procedia Computer Science, vol. 49, no. 1, pp. 50–57, Dec. 2015, 10.1016/j.procs.2015.04.226.
[38] EMO-DB, “Berlin Database of Emotional Speech,” [Online]. Available: http://emodb.bilderbar.info/start.html
[39] Z. T. Liu, M. Wu, W. H. Cao, J. W. Mao, J. P. Xu, and G. Z. Tan, “Speech emotion recognition based on feature selection and extreme learning machine decision tree,” Neurocomputing, vol. 273, pp. 271–280, Jan. 2018, 10.1016/j.neucom.2017.07.050.

[40] M. E. Ayadi, M. S. Kamel, and F. Karray, “Survey on speech emotion recognition: features, classification schemes, and databases,” Pattern Recognition, vol. 44, no. 3, Mar. 2011, 10.1016/j.patcog.2010.09.020.

[41] N. K. Sharma and T. V. Sreenivas, “Time-varying sinusoidal demodulation for non-stationary modeling of speech,” Speech Communication, vol. 105, pp. 77–91, Dec. 2018, 10.1016/j.specom.2018.10.008.

[42] G. Tzanetakis, “Music analysis, retrieval and synthesis of audio signals MARSYAS,” in Proc. Multimedia, Vancouver, British Columbia, Canada, Oct. 2009, pp. 931–932.

[43] T. Özseven and M. Düğenci, “Speech acoustic (SPAC): A novel tool for speech feature extraction and classification,” Applied Acoustics, vol. 136, pp. 1–8, Jul. 2018, 10.1016/j.apacoust.2018.02.009.

[44] D. J. Hemanth, J. Anitha, and L. H. Son, “Brain signal based human emotion analysis by circular back propagation and deep Kohonen neural networks,” Computers & Electrical Engineering, vol. 68, pp. 170–180, May. 2018, 10.1016/j.compeleceng.2018.04.006.

[45] W. Cao, X. Wang, Z. Ming, and J. Gao, “A review on neural networks with random weights,” Neurocomputing, vol. 275, pp. 278–287, Jan. 2018, 10.1016/j.neucom.2017.08.040.

[46] X. Dong and D. X. Zhou, “Learning gradients by a gradient descent algorithm,” J. Mathematical Analysis and Applications, vol. 341, no. 2, pp. 1018–1027, May 2008, 10.1016/j.jmaa.2007.10.044.

[47] F. Luo, W. Guo, Y. Yu, and G. Chen, “A multi-label classification algorithm based on kernel extreme learning machine,” Neurocomputing, vol. 260, pp. 313–320, Oct. 2017, 10.1016/j.neucom.2017.04.052.

[48] A. Lendasse, C. M. Vong, K. A. Toh, Y. Miche, and G. B. Huang, “Advances in extreme learning machines,” Neurocomputing, vol. 261, pp. 1–3, Oct. 2017, 10.1016/j.neucom.2017.01.089.

[49] K. J. Nishanth and V. Ravi, “Probabilistic neural network based categorical data imputation,” Neurocomputing, vol. 218, pp. 17–25, Dec. 2016, 10.1016/j.neucom.2016.08.044.

[50] J. Grim and J. Hora, “Iterative principles of recognition in probabilistic neural networks,” Neural Networks, vol. 21, no. 6, pp. 838–846, Aug. 2008, 10.1016/j.neunet.2008.03.002.

[51] F.-J. González-Serrano, Á. Navia-Vázquez, and A. Amor-Martín, “Training support vector machines with privacy-protected data,” Pattern Recognition, vol. 72, pp. 93–107, Dec. 2017, 10.1016/j.patcog.2017.06.016.

[52] P. P. Dahake, K. Shaw, and P. Malathi, “Speaker dependent speech emotion recognition using MFCC and Support Vector Machine,” in Proc. ICACDOT, Pune, India, 2016, pp. 1080–1084, 10.1109/ICACDOT.2016.7877753.

[53] S. Patoomsiri, C. Vladimir, and K. Boonserm, “Universum selection for boosting the performance of multiclass support vector machines based on one-versus-one strategy,” Knowledge-Based Systems, vol. 159, pp. 9–19, Nov. 2018, 10.1016/j.knosys.2018.05.025.

[54] R. E. Fan, P. H. Chen, and C. J. Lin, “Working set selection using second order information for training support vector machines,” J. Machine Learning Research, vol. 6, no. 4, pp. 1889–1918, Dec. 2005, 10.1115/1.1898234.